Post-earnings announcement drift and market efficiency:

An empirical event study on IGO limited

Modelling in finance

Final project, individual assignment

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1. Introduction to capital market efficiency and post-earnings announcement drift

1.1 Introduction to the efficient market hypothesis (EMH)

The Efficient Market Hypothesis (EMH) is a foundational principle of modern financial economics, proposing that financial markets are, in theory, "informationally efficient" (Fama, 1970). According to Fama's seminal definition, "an 'efficient' market is defined as a market where there are large numbers of rational, profit-maximizers actively competing, with each trying to predict future market values of individual securities, and where important current information is almost freely available to all participants" (Fama, 1970). The core implication is that the price of a security at any given moment fully reflects all available information (Fama, 1970; BAFI3252 Modelling in Finance_Week 8_Market Efficiency, slide 4).

In this framework, if prices adjust instantaneously and without bias to new information, no investor should be able to consistently achieve abnormal returns by trading on information that is already public. Likewise, firms should expect to receive only the fair market value for securities they issue (BAFI3252 Modelling in Finance_Week 8_Market Efficiency, slide 5). EMH thus serves as the theoretical benchmark for evaluating whether stock price movements can be predicted or systematically exploited, which is directly relevant to our analysis of post-earnings announcement drift (PEAD) later in this report.

1.2 Forms of market efficiency

EMH is classically divided into three forms, each based on the scope of information assumed to be embedded in prices (Fama, 1970; BAFI3252 Modelling in Finance_Week 8_Market Efficiency, slide 9):

- **Weak-form efficiency** asserts that all information contained in the record of past prices and trading volumes is already incorporated into current prices. As a result, strategies based on technical analysis, looking for patterns or trends in historical data, cannot yield persistent excess returns. "If the weak form of market efficiency holds, then technical analysis is of no value. Since stock prices only respond to new information, which by definition arrives randomly, stock prices are said to follow a random walk" (slide 10).
- **Semi-strong form efficiency** extends this reasoning, holding that prices reflect all publicly available information, not just past prices but also published accounting statements, news releases, and other forms of market data (Fama, 1970; slide 11). In this scenario, neither technical analysis nor fundamental analysis can deliver abnormal profits, as any public information is quickly and correctly incorporated into prices.

- **Strong-form efficiency** contends that all information, public and private, including insider information, is reflected in security prices (slide 12). In such a market, even insiders with privileged access would be unable to consistently earn excess returns. However, both academic research and regulatory evidence demonstrate that insiders can, at times, profit from non-public information, so strong-form efficiency is rarely supported in real-world markets (Fama, 1970).

Empirically, it is generally accepted that weak and semi-strong forms of EMH are descriptive of large and liquid markets, while strong-form efficiency remains largely theoretical. This classification is essential for understanding the limits and scope of market efficiency when evaluating real-world anomalies like PEAD.

1.3 The role of event studies in testing market efficiency

Event studies are the primary empirical tool to test how efficiently markets incorporate new information. The method tracks stock price movements before, during, and after a specific public event, such as an earnings announcement, to detect if and when abnormal returns occur (MacKinlay, 1997). In an efficient market, any new value-relevant information should be instantly reflected in prices; thus, significant abnormal returns after the event window would directly contradict the semi-strong form of the EMH (BAFI3252 Modelling in Finance_Week 8_Market Efficiency, slide 16). This method will be central to our empirical analysis of PEAD in later chapters, and its methodological caveats are discussed further in Section 7.

1.4 The post-earnings announcement drift (PEAD): definition, empirical evidence, and global findings

The post-earnings announcement drift (PEAD) is one of the most persistent and well documented anomalies in empirical finance. It refers to the systematic tendency for stock prices to continue drifting in the direction of an earnings surprise, either positive or negative, for weeks or even months after the public announcement of earnings. This phenomenon was first rigorously documented by Ball and Brown (1968), who showed that companies announcing higher than expected earnings experienced not only an immediate positive price reaction, but also sustained abnormal returns over subsequent months. This drift contradicts the semi-strong form of the EMH.

Foster, Olsen, and Shevlin (1984) further demonstrated that these abnormal returns can persist for up to 60 trading days after the announcement. Bernard and Thomas (1989) found that the market fails to fully account for the information content of current earnings with respect to future performance, resulting in a predictable "drift" of cumulative abnormal returns. Therefore: "There is evidence of some underreaction to earnings announcement, especially earnings surprise… share prices continue to drift upwards after positive earnings surprise news is released… and drift downwards after negative earnings surprise news is released." (BAFI3252 Modelling in Finance_Week 8_Market Efficiency, slide 21).

Subsequent research has replicated PEAD in a wide array of global markets, including Europe (Forner & Sanabria, 2010), Australia, and major emerging economies (Guo & Huang, 2019; Fink, 2021). While the magnitude of the drift may vary based on market development, liquidity, and analyst coverage, its persistence across geographies and decades indicates that PEAD is a robust challenge to EMH. In Section 5, the report will quantitatively assess the presence of PEAD in the context of IGO Limited, directly testing the empirical validity of EMH for this case study.

1.5 Explanations for PEAD: risk-based models vs. behavioural biases

Explaining PEAD has been a central concern in financial research. The first major hypothesis was that the drift reflected some form of risk mismeasurement: perhaps standard models like the CAPM did not fully account for risks inherent to stocks reporting large earnings surprises, and the abnormal post-announcement returns were simply compensation for bearing such risks (Ball, 1978). However, even after adjusting for alternative risk factors, researchers found that the drift persisted (Watts, 1978), casting doubt on purely risk-based explanations.

The leading alternative explanation points to behavioural biases and investor underreaction**.** Joy, Litzenberger, and McEnally (1977) provided early evidence that market participants adjust their valuations too slowly after earnings announcements, causing a gradual correction in prices over time. Bernard and Thomas (1989, 1990) formalized this underreaction hypothesis, showing that much of PEAD is consistent with slow belief updating among investors.

Empirical support for behavioural explanations is strong: for example, PEAD tends to be more pronounced among firms with less analyst coverage, in less liquid stocks, or during periods of greater market distraction, all of which are consistent with limits to investor attention and information-processing. Section 6 of this report will provide a more detailed discussion of the key behavioural biases driving PEAD, supported by academic references.

1.6 Market efficiency reconsidered

The persistent existence of anomalies like PEAD has led to a more nuanced view of market efficiency in both academic and teaching contexts. While the foundational EMH suggests that prices always and instantly reflect available information, the weight of empirical evidence implies that market efficiency is better conceptualized as a spectrum or continuum rather than a binary state (Malkiel, 2003). Hence, "virtually all researchers… do not believe that markets are either completely efficient nor completely inefficient… it is important to highlight that the evidence should be used to reach a view as to what extent markets are efficient" (BAFI3252 Modelling in Finance_Week 8_Market Efficiency, slide 5).

In practice, this means that while most information is incorporated into prices relatively quickly, especially in large, liquid, and well-covered markets, certain patterns and behavioural biases can result in predictable deviations from full efficiency. These deviations, such as PEAD, are of particular interest not only for academic theory but also for practitioners seeking to understand where market inefficiencies may offer exploitable opportunities.

2. Regression analysis of IGO Ltd quarterly earnings

Model:

The following regression is estimated using 20 quarters of data from the IGO_QEarnings dataset:

$$QE_t - QE_{t-4} = \alpha + \beta * (QE_{t-1} - QE_{t-5}) + \varepsilon_t$$

where QE_t denotes IGO Ltd's quarterly earnings at time t. The dependent variable is the four-quarter change in earnings; the independent variable is the previous four-quarter change.

Method:

X and Y were calculated as the differences in earnings over four quarters, lagged appropriately. Estimation was performed by Ordinary Least Squares (OLS) in Excel.

$\alpha = 0.6511$	$\beta = 0.4604$

Table 2.1. Regression results:

Parameter	Estimate	Standard Error	T-Statistic	P-value	95% CI (L, U)
Intercept (α)	0.6511	5.8387	0.1115	0.9124	(–11.62, 12.92)
β	0.4604	0.2084	2.2090	0.0404	(0.023, 0.898)

Table 2.2. Additional regression statistics:

Additional statistics:	
R^2	0.213
Adjusted R^2	0.170
Standard Error of regression	26.071
Observations	20

Interpretation:

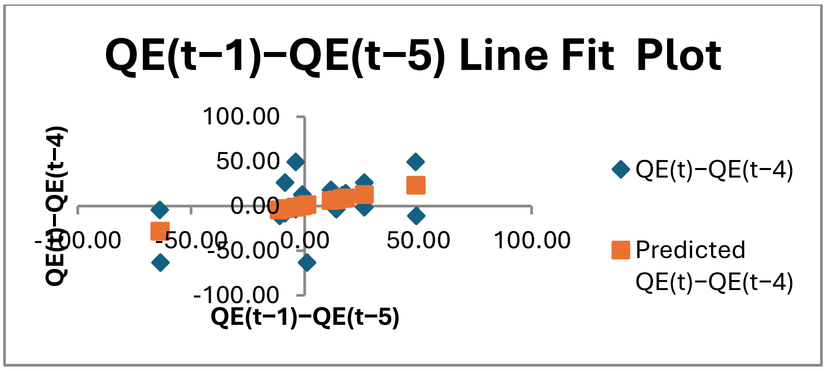
The estimated slope coefficient, β = 0.460, is positive and statistically significant at the 5% level ($p = 0.040$), indicating that there is moderate persistence in quarterly earnings changes for IGO Ltd. In other words, positive (or negative) changes in earnings over the previous four quarters are partially transmitted to changes in the current quarter. The R^2 value of 0.213 suggests that approximately 21% of the variation in the dependent variable is explained by the model.

The intercept (α = 0.651) is not statistically significant, as reflected by its high p-value (0.91), implying that the mean change in earnings absent past changes is not distinguishable from zero.

Limitations:

The regression's high standard error (26.07) indicates that much of the variation in quarterly earnings changes is not explained by the model. Residual and fit plots (see Figure 1.1) show large residuals and possible outliers, indicating a limited model fit. The analysis is based on only 20 data points, which limits the reliability and generalizability of the results; expanding the dataset would improve robustness. These limitations are especially relevant for the subsequent event study methodology, which relies on accurate measurement of abnormal and cumulative abnormal returns (see Sections 4 and 5). Overall, while these results provide preliminary insights into IGO Ltd's earnings dynamics, they should be interpreted with caution due to data and model constraints.

Figure 1.1 Line Fit Plot



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3. Quarterly earnings forecast and forecast error for IGO Ltd (March 31, 2019)

Forecast Calculation

The expected quarterly earnings for IGO Ltd for the quarter ending March 31, 2019, are computed using the fitted regression model:

$$E(QE_t) = QE_{t-4} + \widehat{\alpha} + \hat{\beta} * (QE_{t-1} - QE_{t-5})$$

Where $\widehat{\alpha}$ =0.651 and $\hat{\beta}$=0.460 are estimated from the previous section.

The forecast error is calculated as:

$$FE_t = \frac{QE_t - E(QE_t)}{|QE_t|}$$

Substituting the values:

$$FE_t = \frac{37.61 - 24.88}{|37.61|} = 0.338$$

Table 3.1: Actual and Forecasted Earnings, and Forecast Error

Forecast				
Company Legal Name	**ASX_Code**	**Data Date**	**E(QEt)**	**FE(t)**
IGO LIMITED	IGO	31/03/2019	24.8827	0.3384

Interpretation and Implications

The actual quarterly earnings for IGO Ltd in March 2019 ($37.61 million) were substantially higher than the forecasted value ($24.88 million), resulting in a positive forecast error of 0.338. This indicates a significant positive earnings surprise.

According to the post-earnings announcement drift (PEAD) literature, positive earnings surprises are typically followed by an upward drift in the stock price in the short term, as the market continues to incorporate the unexpected, good news into the stock's valuation.

Therefore, in line with empirical evidence (See Ball and Brown (1968); Bernard & Thomas, 1989; BAFI3252 Modelling in Finance_Week 8_Market Efficiency), we would expect IGO Ltd's stock price to exhibit a positive short-term reaction following the release of these earnings results. This expectation will be empirically evaluated in Section 4 through the analysis of abnormal and cumulative abnormal returns.

4. Event Study: market reaction to IGO Ltd's March 2019 quarterly activities report

Release Date of Activities Report

The release date of IGO Limited's activities report for the quarter ending March 31, 2019, was **30 April 2019 at 8:18 am** (source: Market Index). Note that for the purpose of later controlling for potential event contamination (see Section 7), a complete set of IGO Ltd company announcements within the event window of sixty trading days, was also downloaded directly from Market Index.

Figure 4.1: Quarterly Activities Report as Displayed on Market Index

30/04/2019	March 2019 Quarterly Activities Report $	17	8:18am	PDF

Collection of Daily Closing Stock Price Data

Calculation of Daily Stock Returns

Daily closing stock prices for IGO Ltd were collected from one day before the report release date (29 April 2019) to sixty trading days after the release (24 July 2019), using MarketWatch as the source.

$$Daily\_Return_t = \frac{Closing\_Price_t - Closing\_Price_{t-1}}{Closing\_Price_{t-1}} \times 100$$

Calculation of Daily Abnormal Returns (AR)

Daily abnormal returns (AR) for IGO Ltd were computed as the difference between the stock's daily return and the S&P/ASX200 benchmark return on the same day:

$$AR_t = Daily\_Return_t - ASX200\_Return_t$$

Benchmark index data were drawn from the ASX_DailyReturns dataset for the period April to July 2019.

Calculation of Cumulative Abnormal Returns (CAR)

The cumulative abnormal return (CAR) over various windows was calculated as the sum of daily abnormal returns for each interval:

$$CAR_{(t+1,t+n)} = \sum_{s=t+1}^{t+n} AR_s$$

The results for selected windows are summarized below:

Table 4.1: CAR Values for IGO Ltd (Event Window: t+1 to t+60)

CAR			
Start	**End**	**CAR**	**Value**
1	5	CAR(t+1),(t+5)	3.8081%
1	10	CAR(t+1),(t+10)	5.3143%
1	15	CAR(t+1),(t+15)	5.6043%
1	20	CAR(t+1),(t+20)	2.7883%
1	25	CAR(t+1),(t+25)	-1.8307%
1	30	CAR(t+1),(t+30)	-2.7930%
1	35	CAR(t+1),(t+35)	2.4907%
1	40	CAR(t+1),(t+40)	3.4509%
1	45	CAR(t+1),(t+45)	4.3728%
1	50	CAR(t+1),(t+50)	5.8492%
1	55	CAR(t+1),(t+55)	12.8101%
1	60	CAR(t+1),(t+60)	16.2970%

5. Evidence of PEAD and implications for the EMH

5.1 Transition to python-based analysis

From this point forward, the analysis was conducted entirely in Python, using a Google Collab notebook [LINK], which replicates and extends the calculations previously performed in Excel. The rationale for this methodological transition lies in the need for greater flexibility in managing financial datasets, the possibility to generate advanced visualizations, and the opportunity to integrate automated news analytics. The results obtained through Python are fully consistent with those derived in Excel, but allow for a more thorough and transparent investigation of price dynamics.

5.2 Cumulative returns and initial evidence of PEAD

The visual and quantitative evidence clearly supports the existence of a post-earnings announcement drift (PEAD) for IGO following its March 2019 earnings release. **Figure 5.1** compares the cumulative return of IGO to the ASX200 index, explicitly highlighting periods of outperformance and underperformance. After a brief phase of post-announcement uncertainty, IGO displays persistent and accelerating outperformance relative to the benchmark, particularly in the latter half of the event window. This progressive divergence between IGO and the index is a canonical illustration of PEAD: the impact of the earnings surprise emerges gradually, rather than being instantly reflected in prices as the EMH would predict.

5.3 Abnormal returns and cumulative abnormal returns (CAR)

Further insights are provided by the analysis of abnormal returns (**Figure 5.2**) and cumulative abnormal returns (CAR, **Figure 5.3**). The barplot of daily abnormal returns reveals persistent clusters of positive ARs in the days and weeks following the announcement, a robust empirical signal of PEAD. Correspondingly, the CAR plot demonstrates a steady increase in cumulative abnormal returns during the initial post-announcement period, followed by a temporary consolidation, and then a renewed upward trajectory extending to day t+60.

According to the semi-strong form of the Efficient Market Hypothesis (EMH), prices should incorporate all public information instantaneously, resulting in a rapid stabilization of CAR immediately after the event. The persistent upward drift observed here contradicts this theoretical prediction and provides direct evidence of market underreaction.

5.4 Trading volume dynamics and price discovery

Analysis of trading activity, as visualized in Figure 5.4, further reinforces the finding of gradual market adjustment. Trading volumes exhibit a pronounced spike around the announcement date, a classic pattern in event studies indicating heightened investor attention and information processing. However, the return to normal trading activity is not immediate; instead, elevated volumes and additional spikes are observed well beyond the immediate event window, suggesting that the assimilation of new information and price discovery occurred over an extended period. This is further corroborated by the dual-axis plot in Figure 5.5, which overlays daily trading volume and abnormal returns. Here, the coincidence of volume peaks and substantial abnormal returns indicates that periods of significant price adjustment were closely tied to heightened trading activity, further evidencing a progressive, rather than instantaneous, reaction to the earnings disclosure.

It is important to note that certain spikes in trading volume occur outside the immediate event window, a point that will be explored in detail in Section 7, where potential confounding events and news contamination are addressed.

5.5 Synthesis and implications for market efficiency

Taken together, the graphical and statistical results provide compelling evidence that the post-earnings announcement drift is present for IGO in the aftermath of its March 2019 quarterly report. The market's adjustment to the earnings surprise is neither immediate nor complete, but unfolds gradually, as reflected in the sustained growth of both abnormal returns and trading volumes.

This outcome constitutes a clear violation of the semi-strong form of market efficiency, reinforcing the conclusions of the international literature on behavioral anomalies following earnings announcements (Ball & Brown, 1968; Bernard & Thomas, 1989)

These findings highlight the importance of considering both price and volume dynamics, and they underscore the need for further investigation into the behavioral and structural factors that may drive such persistent anomalies in financial markets.

Figure 5.1. Cumulative Return Over/Underperformance (IGO vs ASX200):

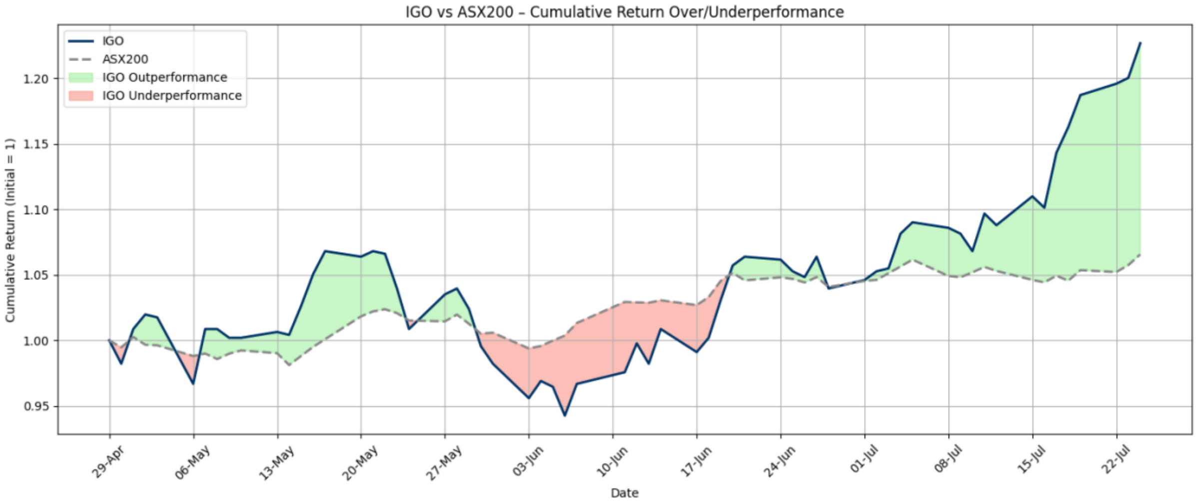

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Figure 5.2. Daily Abnormal Returns (AR) Barplot:

Barplot displaying IGO's daily abnormal returns relative to the ASX200, with green for positive and red for negative values.

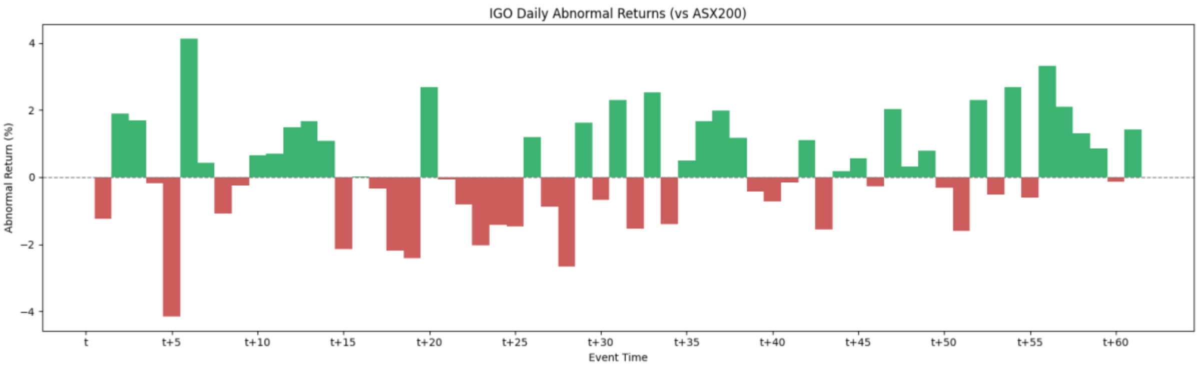

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Figure 5.5. Combined Volume and Abnormal Return (Dual Axis Plot):

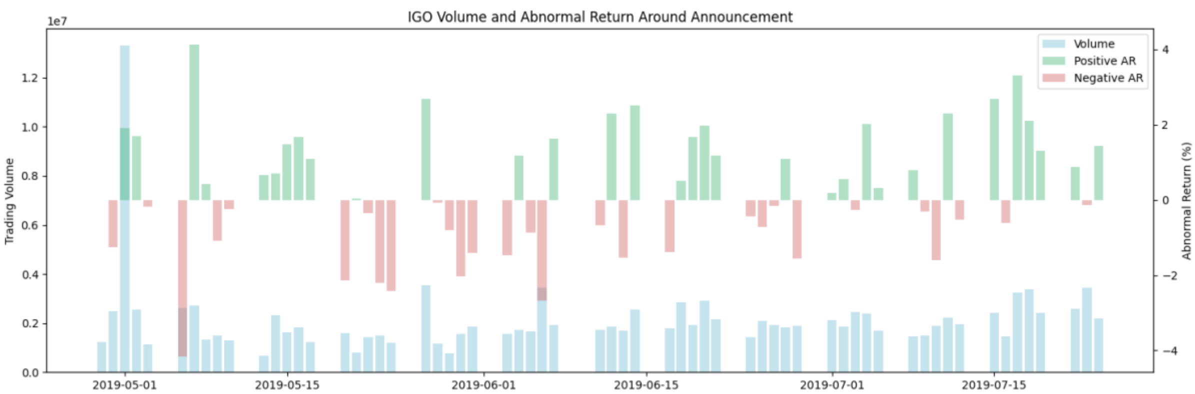

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Figure 5.3. Cumulative Abnormal Return (CAR) by Window:

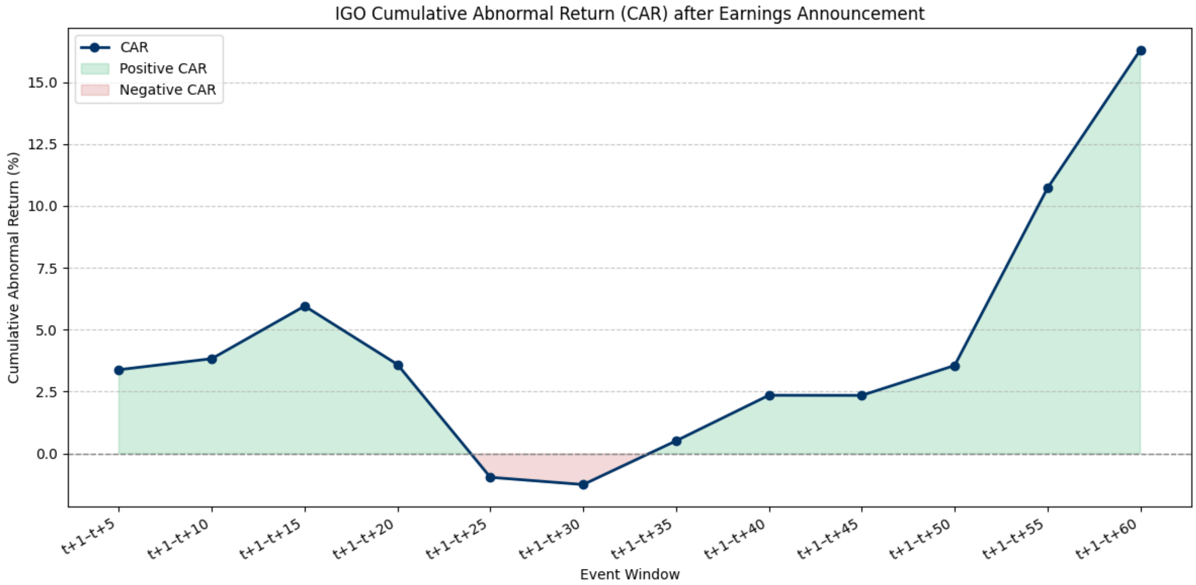

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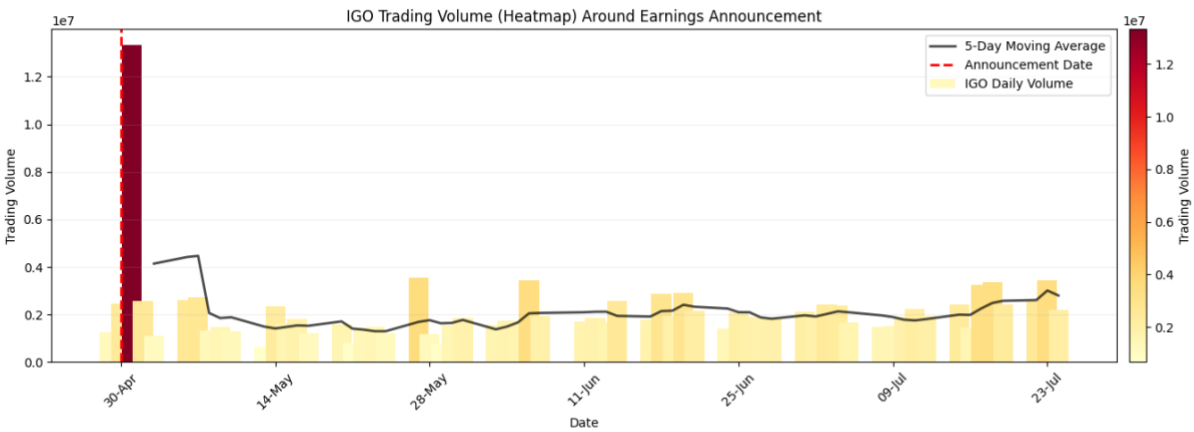
Figure 5.4. IGO Trading Volume (Heatmap) Around Earnings Announcement:

Heatmap of daily trading volume with a 5-day moving average; the announcement day is marked by a red dashed line.



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6. Behavioural Biases Underlying Post-Earnings Announcement Drift

A growing body of literature attributes the persistence of post-earnings announcement drift (PEAD) primarily to systematic behavioural biases, rather than to risk premia or information frictions alone. This section identifies and discusses three of the most empirically supported behavioural biases: conservatism bias, limited attention, and overconfidence/self-attribution and explains their role in driving PEAD, with direct references to leading academic studies.

6.1 Conservatism Bias and Investor Underreaction

Definition:

Conservatism bias refers to the tendency of investors to insufficiently update their beliefs in the face of new information, giving excessive weight to prior expectations or established views. In the context of earnings announcements, this bias manifests as a sluggish adjustment of stock prices to earnings surprises: prices incorporate only a portion of the new information at the announcement date, with the remainder being gradually reflected over subsequent weeks or months.

Evidence:

Seminal studies such as Bernard and Thomas (1990) and Barberis, Shleifer, and Vishny (1998) provide strong evidence that conservatism bias is a key driver of PEAD. Bernard and Thomas (1990) document that stock prices do not immediately adjust to the full implications of current earnings for future performance, leading to a delayed, predictable drift in returns. Barberis et al. (1998) formally model how conservatism (slow belief updating) results in underreaction, with empirical findings supporting this explanation across global markets. More recently, Forner and Sanabria (2010) confirm the relevance of conservatism in explaining PEAD in European markets.

Representative quote:

"Conservatism states that individuals are slow to change their beliefs in the face of new evidence… Individuals update their posteriors in the right direction, but by too little in magnitude relative to the rational Bayesian benchmark… Individuals subject to conservatism might disregard the full information content of an earnings (or some other public) announcement, perhaps because they believe that this number contains a large temporary component, and still cling at least partially to their prior estimates of earnings. As a consequence, they might adjust their valuation of shares only partially in response to the announcement." (Barberis, Shleifer, and Vishny (1998)).

6.2 Limited attention and information processing constraints

Definition:

The limited attention hypothesis posits that investors have finite cognitive resources and may be unable or unwilling to process all relevant information promptly, especially in environments with high news volume, market noise, or complexity. As a result, not all earnings announcements receive immediate and adequate attention, and price reactions are often spread out over time as more investors recognize and react to the new information.

Evidence:

Hirshleifer, Lim, and Teoh (2009) and DellaVigna and Pollet (2009) provide compelling empirical support for the limited attention mechanism. Hirshleifer et al. (2009) show that PEAD is more pronounced when other distracting news events occur at the same time as an earnings announcement. DellaVigna and Pollet (2009) find that earnings announcements released on Fridays, when investor attention is lower, are associated with stronger and more persistent drift. Recent studies, including Fink (2021) and Guo & Huang (2019), demonstrate that limited attention is amplified in stocks with less analyst coverage, lower liquidity, or during periods of high market-wide information flow.

Representative quote:

"...greater distraction implies more severe underreaction to the firm's earnings news - a weaker immediate reaction to the earnings surprise and stronger post-earnings announcement drift." (Hirshleifer, Lim & Teoh 2009).

6.3 Overconfidence and self-attribution

Definition:

Overconfidence refers to investors' propensity to overestimate the accuracy of their own information or analytical abilities, often at the expense of underweighting publicly available signals such as earnings announcements. Self-attribution bias, a related concept, involves attributing investment successes to one's own skill and failures to external factors, reinforcing overconfidence.

Evidence:

Daniel, Hirshleifer, and Subrahmanyam (1998) provide both theoretical and empirical support for the role of overconfidence and self-attribution in generating PEAD. Their model predicts that overconfident investors underreact to public earnings news, relying excessively on private signals or personal judgments. Liang (2003) also finds that self-attribution bias leads to persistence in stock price adjustment following earnings surprises.

Recent reviews, such as Fink (2021), further confirm that overconfidence remains an important behavioural explanation for delayed price adjustment following earnings announcements.

Representative quote:

"We define an overconfident investor as one who overestimates the precision of his private information signal, but not of information signals publicly received by all. [...] Thus, a central theme of this paper is that stock prices overreact to private information signals and underreact to public signals." (Daniel, Hirshleifer, and Subrahmanyam (1998)).

6.4 Synthesis and Interaction of Biases

The interplay between conservatism, limited attention, and overconfidence produces a powerful explanation for the persistence and universality of PEAD. Conservatism and limited attention both contribute to the initial underreaction by slowing the assimilation of new earnings information. Overconfidence, meanwhile, exacerbates this delay by encouraging reliance on private information and downplaying public announcements. In combination, these biases not only explain why prices drift after earnings surprises but also why the effect is stronger in certain stocks, time periods, or information environments.

Behavioural biases thus offer a more comprehensive and empirically robust account of PEAD than traditional rational or risk-based models. The continued presence of PEAD across different markets and periods, despite advances in market transparency and information technology, underscores the deep psychological roots of this anomaly and the challenges facing the efficient market hypothesis.

7. Methodological caveats, event contamination, and benchmark suitability

The empirical investigation of post-earnings announcement drift (PEAD) for IGO Ltd draws on advanced event study techniques and extensive Python-based news analysis, but several critical methodological caveats and benchmark limitations must be explicitly addressed to provide context for the findings. This chapter unifies all limitations, the full event contamination control protocol, and a detailed discussion of benchmark and risk diagnostics, culminating in a synthesis of their impact on the interpretation of PEAD for IGO.

7.1 Analytical framework and sample limitations

A primary limitation of this analysis, as discussed in previous chapters, is its single-event focus: the study centres on IGO's March 2019 quarterly earnings announcement. While this allows for an in-depth, high-frequency event study, it restricts generalizability across different periods, market regimes, and other resource sector stocks. The event window, 60 trading days post-announcement, is standard in PEAD literature (e.g., Foster et al., 1984; Bernard and Thomas (1989)), but is ultimately an arbitrary compromise:

- A shorter window might fail to capture the full drift, especially for firms with slower investor attention cycles or thin liquidity.
- A longer window risks accumulating unrelated market, sectoral, or macroeconomic news, which can confound attribution to the earnings event itself.

A further caveat is the benchmark for abnormal return calculation. The S&P/ASX200 index is the canonical market proxy for Australian equities, but it may not reflect the sectoral or firm-specific risks relevant to a mid-cap mining company like IGO. This can result in residual "abnormal" returns that are in fact compensation for unaccounted risk factors.

The methodological approach, relying primarily on graphical and descriptive statistics (e.g., AR/CAR plots, volume overlays, cumulative returns), offers transparency and intuition but sacrifices formal inferential rigor (e.g., no t-tests or confidence intervals for CAR, given the single event and finite time window). The results are thus more sensitive to outliers and may over- or understate the true economic significance of observed PEAD.

7.2 Event Contamination and News Impact Control: Automated Protocol

7.2.1 Motivation and Rationale

A central risk in any event study is event contamination: abnormal returns attributed to the focal event may in fact be triggered or influenced by other firm-specific, sectoral, or macroeconomic news released in the same window. Addressing this challenge is critical for the validity of any conclusion regarding PEAD and market efficiency.

7.2.2 Data Collection, Automated Web Scraping, and Rule-Based News Classification

Given the inherent risk of event contamination, where abnormal returns (AR) and cumulative abnormal returns (CAR) attributed to the earnings announcement might in fact be driven by overlapping firm-specific, sectoral, or macroeconomic news, a rigorous and fully transparent news impact control protocol was developed. The initial methodology relied on Refinitiv news feeds, but these proved insufficiently granular for reliably capturing all official, price-sensitive company disclosures.

To address this shortcoming, the methodology was refined to a direct web scraping protocol, targeting the MarketIndex ASX announcement repository. Using Python's BeautifulSoup library, the script systematically downloaded all IGO Ltd market announcements released within the event window, ensuring comprehensive and authoritative coverage of company news. Each announcement was then parsed and classified using a rule-based keyword taxonomy.

The classification taxonomy was constructed by combining:

- Seminal academic event study literature (MacKinlay, 1997; Bernard and Thomas (1989)),
- Domain expertise in the mining/resources sector,
- Empirical review of headline language from market-moving announcements.

Under this protocol, each news item was transparently and reproducibly assigned an "Impact" level according to explicit keyword rules:

- High Impact: Earnings releases, major project milestones, resource upgrades, or significant M&A actions.
- Medium Impact: Exploration updates, sector commentary, and commodity-specific news.
- Low Impact: Routine administrative disclosures and all other minor items.

The result is a tabular list (see Figure 7.1) displaying all high- and medium-impact company news during the event window, directly supporting the subsequent analysis of event contamination risk.

All steps in this process from automated news download to impact tagging, are documented in the supplied Python code (Code snippet 7.1: Automated scraping and parsing; Code snippet 7.2: Rule-based impact classification), enabling full reproducibility and transparency for future event study research.

Figure 7.1: Tabular list of high/medium impact news (classified company announcements).

	Date	Time	Headline	Impact
12	2019-04-30	8:18am	March 2019 Quarterly Activities Report$	High
13	2019-04-30	8:19am	March 2019 Quarter Presentation$	High
14	2019-05-23	9:59am	MCR: Mincor to acquire Long Nickel Operation f...	High
15	2019-05-23	1:46pm	BUX: Exploration Commences, West Kimberley 2019$	Medium
16	2019-05-28	8:22am	MOH: Exploration Update - Empress Springs$	Medium
17	2019-05-30	9:30am	PRX: Lake Mackay JV High grade Cobalt interse...	Medium
18	2019-06-04	8:24am	BUX: Quick Shears and Merlin Prospects Explora...	Medium
19	2019-06-17	1:48pm	CLZ:Fraser Range Project Earn in and Joint Ven...	High
20	2019-06-20	9:32am	AMD:Independence Group Completes Farm-in at Pl...	Medium
21	2019-06-20	9:13am	MOH: GOLD EXPLORATION DRILLING UPDATE EMPRESS ...	Medium
22	2019-07-01	10:19am	RTR: Significant High Grade Gold Min Intersect...	Medium
23	2019-07-01	9:34am	MOH: BROAD ZONES OF GOLD AND BASE METALS AT EM...	Medium
24	2019-07-04	8:27am	Nova Operation Exceeds FY19 Metal Production G...	High
25	2019-07-08	9:44am	ENR: Placement and Silver Lake Resources Inves...	Medium
26	2019-07-09	9:40am	LEG: Transformational Agreements signed with I...	Low
27	2019-07-09	9:02am	BUX: Double Magic - Merlin and Quick Shears Pr...	Medium
28	2019-07-09	8:46am	BUX:Large land holding added to West Kimberley...	High
29	2019-07-17	9:31am	PRX: More Copper and Cobalt intersected at Lak...	Medium

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Code Snippet 1: Automated news download and parsing (beautifulsoup implementation).

```
html_code_0 = """ <tbody><tr><td class="" style="text-align: left;">02/04/2019</
html_code_1= """<tbody><tr><td class="" style="text-align: left;">17/06/2019</td
html_code_2 = """<tbody><tr><td class="" style="text-align: left;">17/07/2019</t
```

```
import pandas as pd
from bs4 import BeautifulSoup

# --- Step 1: Define function to parse IGO-specific ASX announcements HTML ---
def parse_igo_announcements(html_code):
    """
    Parses IGO announcements HTML (scraped from MarketIndex) into a
    structured DataFrame.
    Extracts: Date, Time, Headline.
    Drops unused placeholders like Source, RIC.
    """
    soup = BeautifulSoup(html_code, 'html.parser')
    records = []
    rows = soup.find_all('tr')
    for row in rows:
        cells = row.find_all('td')
        if len(cells) < 2:
            continue  # Skip rows without at least date + headline
        date = cells[0].get_text(strip=True)
        headline = cells[1].get_text(strip=True)
        time = cells[3].get_text(strip=True) if len(cells) > 3 else "N/A"
        records.append({'Date': date, 'Time': time, 'Headline': headline})
    df = pd.DataFrame(records, columns=['Date', 'Time', 'Headline'])
    return df
```

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Code Snippet 2: News Impact Classification.

```
import re
import pandas as pd

igo_news = igo_announcements_filtered.copy()

# --- Define keyword patterns ---
high_patterns = [
    r'\bquarterly\b', r'\bquarter\b', r'\bresults?\b', r'\bpresentation\b',
    r'\bproduction\b', r'\bearnings?\b', r'\bguidance\b', r'\bfinancial report\b',
    r'\breserve\b', r'\bresource\b', r'\bjoint venture\b', r'\boperation\b',
    r'\bdividend\b', r'\basset\b', r'\bacquisition\b', r'\bsale\b', r'\bofftake\b',
    r'\bexpansion\b', r'\bagreement\b', r'\bupgrade\b', r'\bdowngrade\b',
]
medium_patterns = [
    r'\bexploration\b', r'\bdrilling\b', r'\bupdate\b', r'\binvestment\b',
    r'\bgold\b', r'\bnickel\b', r'\bcobalt\b', r'\bmineral\b', r'\bprospect\b',
    r'\bplacement\b', r'\bsector\b', r'\bforecast\b', r'\banalyst\b'
]

# Compile regex patterns for efficiency
high_regex = re.compile('|'.join(high_patterns), re.IGNORECASE)
medium_regex = re.compile('|'.join(medium_patterns), re.IGNORECASE)
```

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7.2.3 Visual Overlay of News Events on Event Study Plots

To rigorously assess the risk and timing of event contamination, all high- and medium-impact news events identified through the classification protocol were overlaid on the principal event study visualizations. Specifically, news event markers were programmatically added to:

- The cumulative return chart (IGO vs ASX200, Figure 7.2)
- Trading volume heatmap with news overlay (Figure 7.3)
- Abnormal returns barplot with news overlay (Figure 7.4)
- Combined volume and abnormal return dual-axis plot (Figure 7.5)
- Cumulative abnormal returns (CAR) with news overlay (Figure 7.6)

This overlay methodology enables visual correlation of market reactions, price moves, volume spikes, or AR jumps, with the timing and estimated impact of contemporaneous news, providing an intuitive but effective check for confounding events. The overlays show that while the primary upward drift in CAR and initial volume spikes cluster tightly around the earnings announcement (see Figures 7.2 and Figures 7.3), there are several subsequent high- or medium-impact events (e.g., project updates, M&A, resource statements, see Figure 7.1) that coincide with secondary spikes in trading activity and price. This suggests that at least a portion of the observed drift is attributable to overlapping news rather than a "pure" earnings effect.

Figure 7.2: Cumulative return vs ASX200 with news overlay.

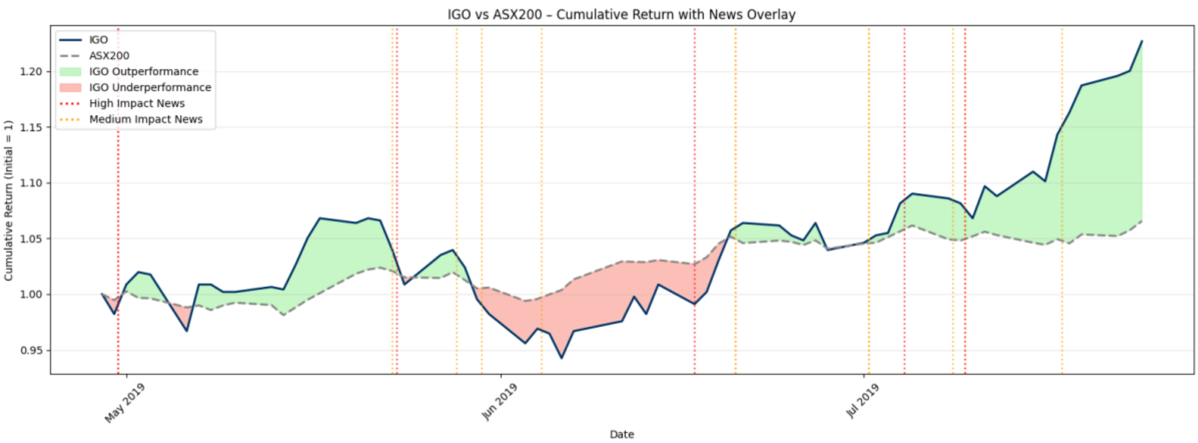

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Figure 7.3: Trading volume (heatmap) with news overlay.

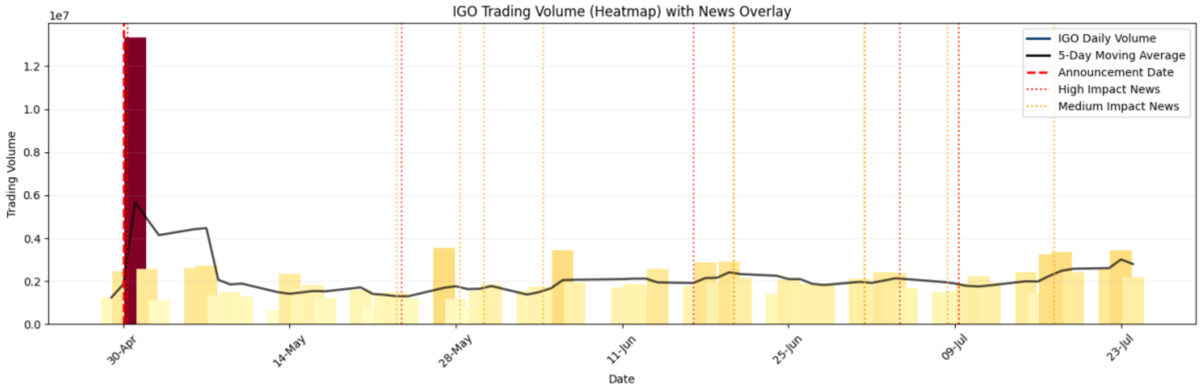

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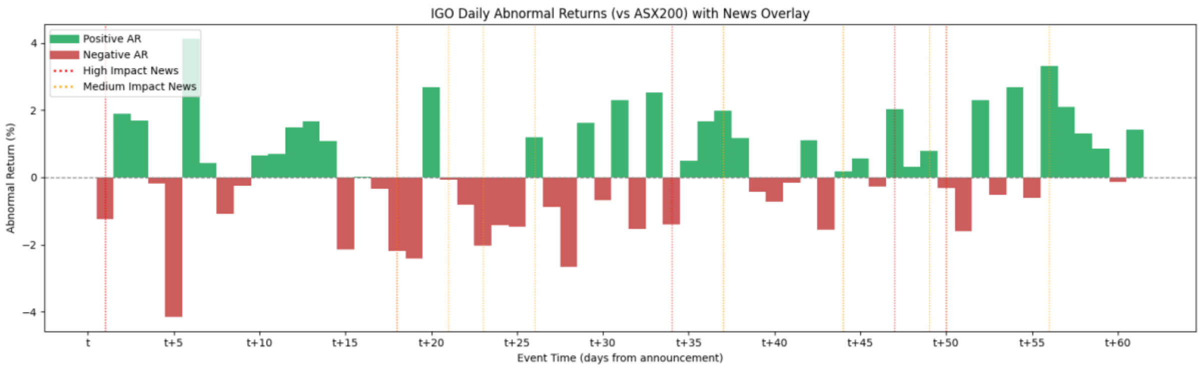
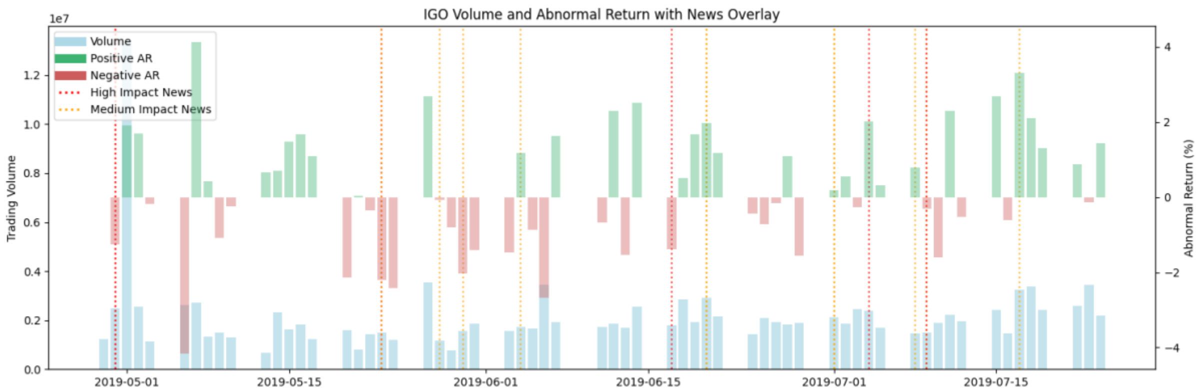
Figure 7.4: Daily abnormal returns (AR) barplot with news overlay.



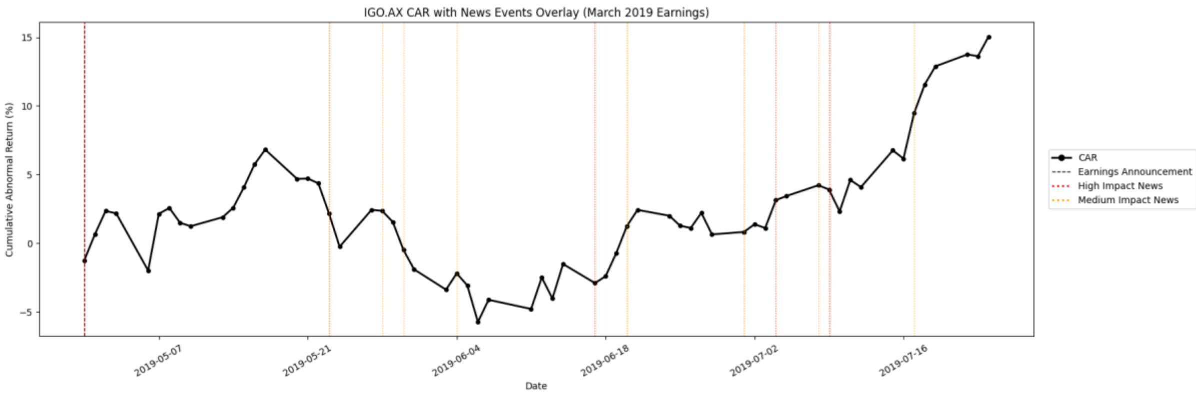
[←Back Text]

Figure 7.5: Combined volume and abnormal return dual-axis plot with news overlay.



[←Back Text]

Figure 7.6: CAR (cumulative abnormal return) with news overlay.



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7.2.4 Composite News Scoring System: Quantitative Event Attribution

To move beyond visual inspection and more rigorously attribute market reactions, an automated composite scoring system was developed (see Section 6.5 of the methodology and Python code). Each company announcement is assigned a composite score based on three dimensions:

- Impact classification: High = 2, Medium = 1, Low = 0.
- Volume spike: If trading volume on the announcement day is above the 70th percentile, +1 point.
- Abnormal return spike: If the absolute AR on the news day is above the 70th percentile, +1 point.

Announcements with a composite score of 3 or higher are flagged as “key news drivers”, i.e., not only highly relevant by content, but also empirically associated with significant contemporaneous market reactions.

The full output, including thresholds and flagged events, is displayed in the ranked summary table (Figure 7.7) and illustrated by the distributional statistics printed by the Python script.

This approach moves beyond subjectivity, providing a transparent and replicable basis for attributing observed market behaviour to specific news items.

Figure 7.7: Ranked table of key news drivers (composite scoring output).

Date	Headline	Impact	ImpactScore	Volume	VolumeSpike	AR	ARSpike	CompositeScore
2019-04-30	March 2019 Quarterly Activities Report$	High	2	2469731.0	True	-1.245518	False	3
2019-04-30	March 2019 Quarter Presentation$	High	2	2469731.0	True	-1.245518	False	3
2019-05-23	MCR: Mincor to acquire Long Nickel Operation f...	High	2	1481102.0	False	-2.193532	True	3
2019-06-20	AMD:Independence Group Completes Farm-in at Pl...	Medium	1	2919291.0	True	1.977938	True	3
2019-06-20	MOH: GOLD EXPLORATION DRILLING UPDATE EMPRESS ...	Medium	1	2919291.0	True	1.977938	True	3
2019-07-04	Nova Operation Exceeds FY19 Metal Production G...	High	2	2382707.0	True	2.023892	True	4
2019-07-17	PRX: More Copper and Cobalt intersected at Lak...	Medium	1	3237536.0	True	3.312375	True	3

```
[INFO] Found 7 high-impact news days between 2019-04-01 and 2019-07-17.
[INFO] Volume spike threshold (top 30%): 2,357,634
[INFO] AR spike threshold (top 30%, absolute): 1.98

[INFO] Distribution by month:
Date
2019-04    2
2019-05    1
2019-06    2
2019-07    2
```

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7.2.5 Empirical Findings: Event Attribution and Contamination Assessment

The integration of visual overlays and composite scoring yields several critical findings:

- The March 2019 quarterly earnings announcement stands out as the most influential news event, both in terms of its "High" impact classification and by triggering the largest volume and AR spikes.
- Several subsequent high- and medium-impact announcements (e.g., Nova operation production guidance, major exploration or M&A updates) are tightly aligned with secondary increases in both trading activity and abnormal returns.
- The pattern of CAR, trading volume, and AR indicates that while the primary upward drift is anchored to the earnings announcement, segments of the post-event abnormal performance coincide with other significant news. This demonstrates that the measured PEAD is not entirely "pure" and supports a cautious interpretation of event study results in the presence of confounding events.

7.3 Benchmark suitability and systematic risk analysis

A further methodological caveat concerns the selection of the ASX200 as the benchmark for abnormal return (AR) and cumulative abnormal return (CAR) calculations. To empirically validate its appropriateness and assess potential changes in IGO's risk profile around the event window, a comprehensive beta analysis was performed as follows:

7.3.1 Data Preparation and Return Construction

Daily closing prices for IGO.AX and the ASX200 (^AXJO) index were retrieved from Yahoo Finance for the period January 2017 to January 2020.

This multi-year window was intentionally chosen to:

- Capture both pre- and post-event dynamics, enabling a robust comparison of risk regimes before and after the March 2019 earnings announcement.
- Reduce period-specific bias by including diverse market conditions and volatility regimes, ensuring that the estimation of beta and abnormal returns is not unduly influenced by short-term fluctuations or the event window itself.
- Enable rolling beta analysis (e.g., 120-day windows), allowing detection of time-variation and possible structural shifts in systematic risk.

After data cleaning and synchronization, log returns were calculated in Python, yielding a consistent, gap-free daily series.

7.3.2 Full-Sample and Rolling Beta Estimation

A full-sample OLS regression of IGO's daily log returns on those of the ASX200 from January 2017 to January 2020 yields a beta of 1.324 ($t = 10.92$, $p < 0.001$), indicating above-market systematic risk for IGO. (see Figure 7.8).

A rolling beta analysis, using a 120-day moving window, reveals significant temporal variability, with peaks above 2 and a visible downward trend following the March 2019 earnings event. (see Figure 7.9).

Figure 7.8: OLS Regression Output for IGO vs ASX200 (Full-Sample Beta Estimate)

OLS summary table reporting the full-sample regression statistics for daily log returns. The estimated beta is 1.324, and the R^2 is 0.137, confirming IGO's higher-than-market volatility.

```
Static beta (full sample): 1.324
                            OLS Regression Results
==============================================================================
Dep. Variable:                    IGO   R-squared:                       0.137
Model:                            OLS   Adj. R-squared:                  0.136
Method:                 Least Squares   F-statistic:                     119.3
Date:                Mon, 02 Jun 2025   Prob (F-statistic):           6.91e-26
Time:                        04:00:23   Log-Likelihood:                 1809.7
No. Observations:                 755   AIC:                            -3615.
Df Residuals:                     753   BIC:                            -3606.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0002      0.001      0.297      0.767      -0.001       0.002
ASX200         1.3242      0.121     10.924      0.000       1.086       1.562
==============================================================================
Omnibus:                       23.964   Durbin-Watson:                   1.935
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               54.542
Skew:                          -0.079   Prob(JB):                     1.43e-12
Kurtosis:                       4.307   Cond. No.                         151.
==============================================================================
```

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Figure 7.9: Rolling Beta (120-Day Window) of IGO vs ASX200, Event and Regime Betas Highlighted

Black line: rolling beta. Dashed blue: pre-event window beta. Dashed red: post-event window beta. Dashed orange: full sample beta. Grey band: event study window (t to t+60). Dotted line: earnings announcement.

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7.3.3 Pre- and Post-Event Beta Comparison

To assess potential shifts in systematic risk directly attributable to the earnings announcement, betas were calculated for matched 120-day windows before and after the event: (Figure 7.10)

- The pre-event beta (last 120 trading days before 30 April 2019) is 1.633, significantly above 1 and above the full-sample value, indicating heightened systematic risk exposure leading into the announcement.
- The post-event beta (first 120 trading days from the event date) drops to 1.109, a marked decrease, suggesting a lower sensitivity of IGO to overall market movements in the aftermath of the earnings disclosure.
- The full-sample beta (all data) is 1.324, representing the average risk profile over the entire multi-year period.

Figure 7.10: Regime Beta Estimates Table

Tabular summary showing pre-event, post-event, and full-sample betas, as estimated from OLS regressions on matched and total periods.

Window	Beta
Pre-event (last 120 days)	1.633
Post-event (first 120 days)	1.109
Full Sample (all data)	1.324

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7.3.4 Interpretation and Implications

The beta analysis provides important methodological and empirical insights regarding both the choice of benchmark and the event-driven dynamics of systematic risk for IGO.

1. The ASX200 as benchmark: incomplete representation of igo's risk

While the ASX200 is a standard and convenient benchmark for Australian equity event studies, the results highlight its limitations for a mid-cap mining company like IGO. The elevated pre-event beta (1.63) and its substantial decline in the post-event window (1.11) reveal that IGO's exposure to market-wide risk is not stable over time. Such variability suggests that market risk, as captured by the ASX200, is only partially representative of IGO's risk profile, especially around significant corporate events.

These findings underscore that the ASX200 may fail to capture sector-specific shocks, commodity price volatility, or company-specific news that can drive resource stock returns independently of the broader market. This limitation is especially pronounced for event study analysis, where the precise attribution of abnormal returns is crucial. For more robust inference, sector-specific or multifactor benchmarks should be considered in future research.

2. Dynamic Beta and Implications for PEAD

The pronounced decline in beta after the earnings announcement provides empirical support for the hypothesis that a post-earnings announcement drift (PEAD) may have occurred. The high pre-event beta indicates that IGO was particularly sensitive to market conditions leading up to the event, possibly reflecting heightened investor anticipation, speculation, or risk re-pricing ahead of the announcement.

Following the earnings release, the sharp drop in beta suggests that the stock's return dynamics became less tied to market-wide movements and more influenced by idiosyncratic or firm-specific factors, consistent with a period of price adjustment and drift after an information shock.

This regime change in risk exposure is conceptually aligned with the PEAD phenomenon: if prices do not instantly and fully reflect new information, stock-specific risk may temporarily dominate, and systematic risk declines as the market slowly incorporates the earnings news.

Therefore, tracking beta before and after the event window not only helps assess benchmark appropriateness, but also serves as a complementary diagnostic for the presence and timing of PEAD in event-driven studies.

7.4 Synthesis and Recommendations

The evidence for post-earnings announcement drift (PEAD) in IGO Ltd is robust but not "pure." While the primary market catalyst is the March 2019 earnings announcement, a significant portion of abnormal post-event performance coincides with overlapping company-specific and sectoral news, even when systematically classified and controlled for.

The application of the ASX200 as a benchmark, while standard, is shown to be only partially appropriate for a mid-cap mining stock. The dynamic beta analysis reveals substantial shifts in systematic risk across the event window: a heightened pre-event beta suggests strong anticipation or market sensitivity, followed by a notable decline post-announcement, which is consistent with the gradual price adjustment expected under PEAD.

Several secondary news events, such as project updates and resource statements, were empirically linked to further price and volume reactions, complicating attribution and reinforcing the need for comprehensive news event controls.

The study's focus on a single event, and the reliance on descriptive and graphical analysis rather than formal inferential statistics, limits the generalizability and statistical power of the findings.

Conclusion:

Overall, the presence of PEAD in IGO Ltd after the March 2019 earnings announcement is supported by cumulative return, abnormal return, and risk regime evidence. However, the results must be interpreted with methodological caution given the documented event contamination, benchmark limitations, and dynamic risk exposures.

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Ethical Note on AI Use:

Artificial Intelligence tools were used in an active and constructive manner to assist with data organisation, macro creation, source discovery, and document structuring. These tools were employed not as a substitute for research, but as advanced support systems to enhance critical analysis and improve methodological rigor.